CERES Clouds Working Group Report

W. L. Smith, Jr.
NASA Langley Research Center, Hampton, VA

S. Sun-Mack (modis/viirs lead), Q. Trepte (mask), G. Hong (models), P. Minnis (supreme advisor), D. Painemal (val),
Y. Chen (clr props, test runs), C. Yost (val, mask), R. Smith (proc.), R. Brown (QC),
R. Palikonda (GEO lead), S. Bedka (retrievals, val), D. Spangenberg (everything), M. Nordeen (GEO),
B. Scarino (cal, Tskin, GEO), F-L. Chang (CO2, corrk), Cecilia Wang (machine learning)
T. Chee (IT), E. Heckert (web), B. Shan (GEO), Churngwei Chu (web)
SSAI, Hampton, VA

L. Nguyen (IT lead, GEO), *NASA Langley Research Center*
P. Heck (retrieval code), *CIMSS, UW-Madison*
P. Yang (ice models), Texas A& M University

Thanks to Dave Doelling and his TISA/calibration teams!

Earth Radiation Budget Workshop, Hambuurg, Germany, 12-14 October 2022

Cloud Working Group Objectives

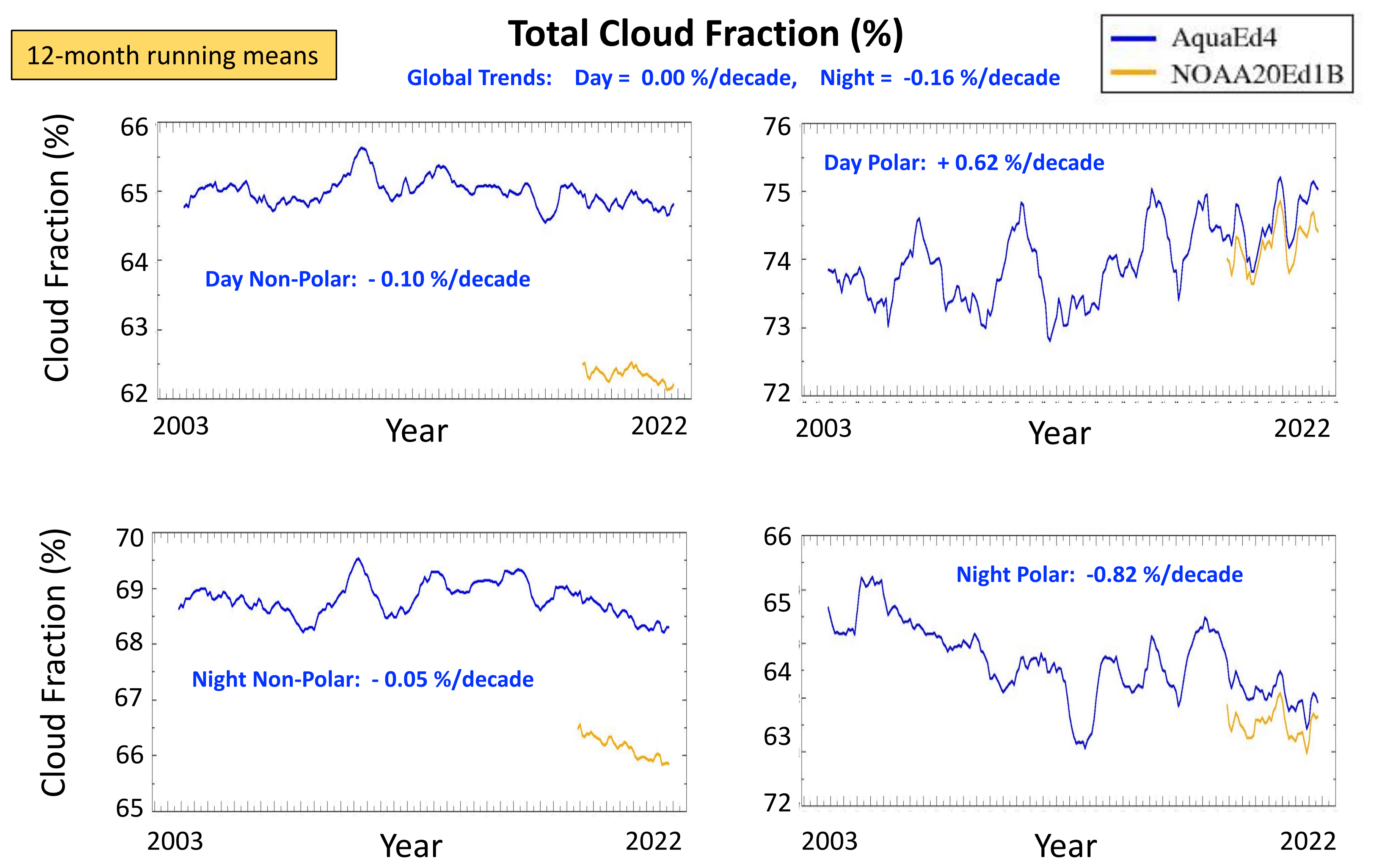
Produce pixel-level cloud properties from LEO & GEO imager radiances

- Include cloud mask, thermodynamic phase, optical depth, effective radius, temperature, height, etc.
- Must be inferred at high resolution within coarser CERES footprints even under the most difficult conditions (e.g. at night, over snow/ice, in the presence of thin cirrus and heavy aerosols)
- Used in CERES processing to convert measured radiances to TOA radiative fluxes, to compute surface fluxes, and to improve the time interpolation of radiative fluxes.
- Must be as spatially and temporally consistent as possible across platforms in order to minimize discontinuities in the CERES CDR

Clouds Processing Status (MODIS & VIIRS)

CERES-MODIS Edition 4 (*CDR)	*Aqua: Jul 2002 – Aug 2022 (~ 20 y)* *Terra: Feb 2000 – Aug 2022 (~ 22.5 y)*	• ***Uses frozen Ed4 cloud codes delivered in 2013*** • ***MODIS Collection 5 radiances thru Feb 2016,*** • ***MODIS Collection 6.1 March 2016 – present and scaled to C5 for consistency over entire record*** • ***Terra-MODIS normalized to Aqua-MODIS (Sun-Mack, et al. 2018)***
CERES-VIIRS Edition 1A	*SNPP: Jan 2012 – Jul 2021 (~ 9.5 y)* *NOAA-20: Jan 2018 – Jul 2021 (~ 3.5 y)*	• ***Uses VIIRS Ed1A cloud code*** • ***SNPP uses forward processing calibrations (C1 radiances), not scaled to MODIS; has discontinuity ~2016 due to a calibration update by SIPS*** • ***N20 uses C2 radiances and scaled to MODIS C5***
CERES-VIIRS Edition 2A	*SNPP: Jan 2012 – Jul 2022 (~ 10.5 y)*	• ***Uses VIIRS Ed1A cloud code*** • ***Uses C2 radiances and scaled to MODIS C5***
CERES-VIIRS Edition 1B (*CDR)	*NOAA-20: Jan 2018 – Aug 2022 (~ 4.5 y)*	• ***Uses new version of VIIRS cloud code (temporary continuity version until Ed5 is released)*** • ***Fills Aqua-MODIS gap in Aug 2020***

Aqua MODIS and NOAA-20 VIIRS Cloud Fractions, 2002-2022



On average, no global trends in cloud fraction since 2002

Non-polar (60N – 60S) trends show very small decrease over 20 years

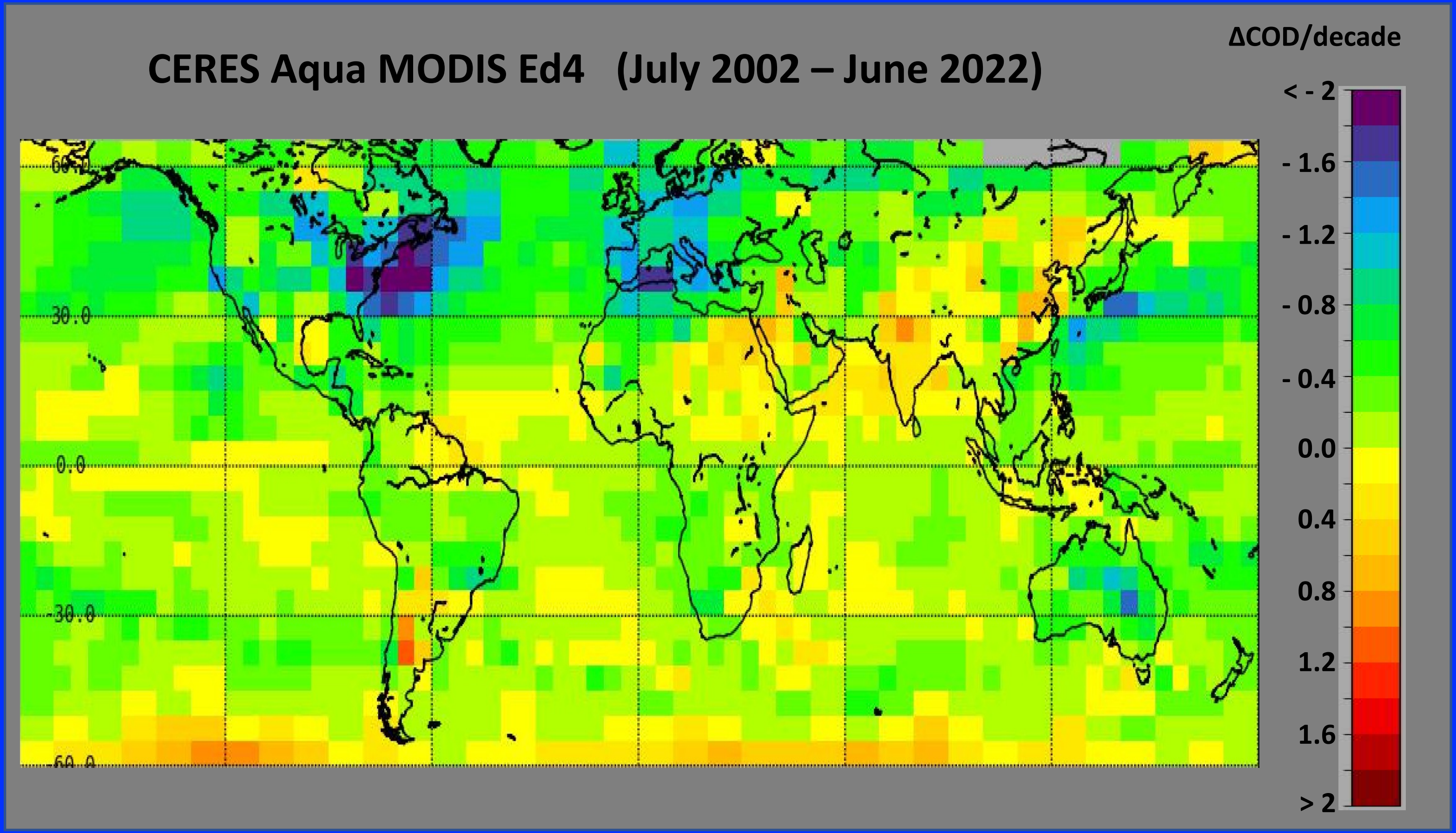
- A decrease over the past 5-10 years is more significant, especially at night. NOAA2-20 tracks this well.

In polar regions, day and night (or summer and winter) have opposite trends.

- Daytime polar cloud mask more trustworthy than nighttime

VIIRS tracks Aqua well but there are significant discontinuities for non-polar regions.

Regional Trend of Total Cloud Optical Depth
(ΔCOD per decade)



- **Large negative trends in total COD over the eastern U.S. and downwind over the adjacent Atlantic – magnitudes remarkable compared to other areas**
- **Corresponding increases in R_e, decreases in N_d, and decreases in reflected SW were also found.**
- **Changes are well correlated with changes in pollution and sulfate aerosols as observed from satellites and characterized in MERRA-2 reanalyses rather than with changes in cloud fraction or meteorology (EIS).**

High confidence that these COD changes are real and not a processing or calibration artifact thanks to the stability of the MODIS radiances and the consistent algorithm approach applied throughout the record

Ed5 Cloud Algorithm Development

Cross-platform consistency and continuity are a primary objective

- MODIS and VIIRS algorithms will be as consistent as possible and use 11 common channels
- The same is true for the CERES-GEO algorithms which operate on more than 20 satellites, but the common denominator is just a few channels (0.63, 3.9, 11, 6.7 µm) except for Met-5, Met-7, and GMS-5 (0.63, 11 µm)
- Ed5 will also have many bug fixes, updated cloud models, atmospheric corrections and ancillary datasets (e.g. snow/ice maps, clear sky radiances) to improve accuracies and consistency
- Ed5 algorithm development framework employs information from the GEOS-IT to keep pace with latest GMAO reanalysis systems

MODIS Central Wavelength (µm)	VIIRS Central Wavelength (µm)
0.65	0.64
1.61	1.61
2.13	2.26
3.78	3.74
11.0	10.8
12.0	12.0
8.55	8.55
1.24	1.24
0.47	0.49
1.38	1.38
0.86	0.86
~~6.71~~	N/A
~~13.3~~	N/A

Status on these mostly unchanged since last meeting

Exploring the use of AI/ML methods to address satellite cloud remote sensing challenges

Problem Areas	AI/ML Approach
Image quality – bad scan lines in GEO radiance imagery	Apply human visual or **CNN** QC for most cases and satellites; apply radiance reconstruction using **KNN** for severely corrupted images
Day and night cloud optical properties are inconsistent	**ANN** to help overcome theoretical limits due to IR blackbody limit; **KNN** to extrapolate optical properties from daytime
Artifacts in the solar terminator and sun-glint	**KNN** to extrapolate information from surrounding space/time domain
Often poor assumption that clouds are single-layer, vertically homogeneous	New parameterizations that better account for cloud vertical structure; **ANN** for multi-layer cloud retrieval methods
Poor knowledge of land surface emission temperature (affects cloud mask and retrievals)	**DNN** to correct model reanalysis skin temperature based on correlations with satellite-derived values in clear conditions
Nighttime cloud detection difficult in polar regions	**ANN** trained with CALIPSO data for application to MODIS/VIIRS
Estimating cloud geometric thickness and base height	**ANN** to better capture signals from satellite and ancillary info

Image Quality – bad scan lines

Problem:

- Unmitigated bad scanlines may contain radiance values within valid range that can negatively impact derived data products
- Manually searching and flagging these is laborious and expensive but undertaken for a long time to minimize impacts to CERES CDR

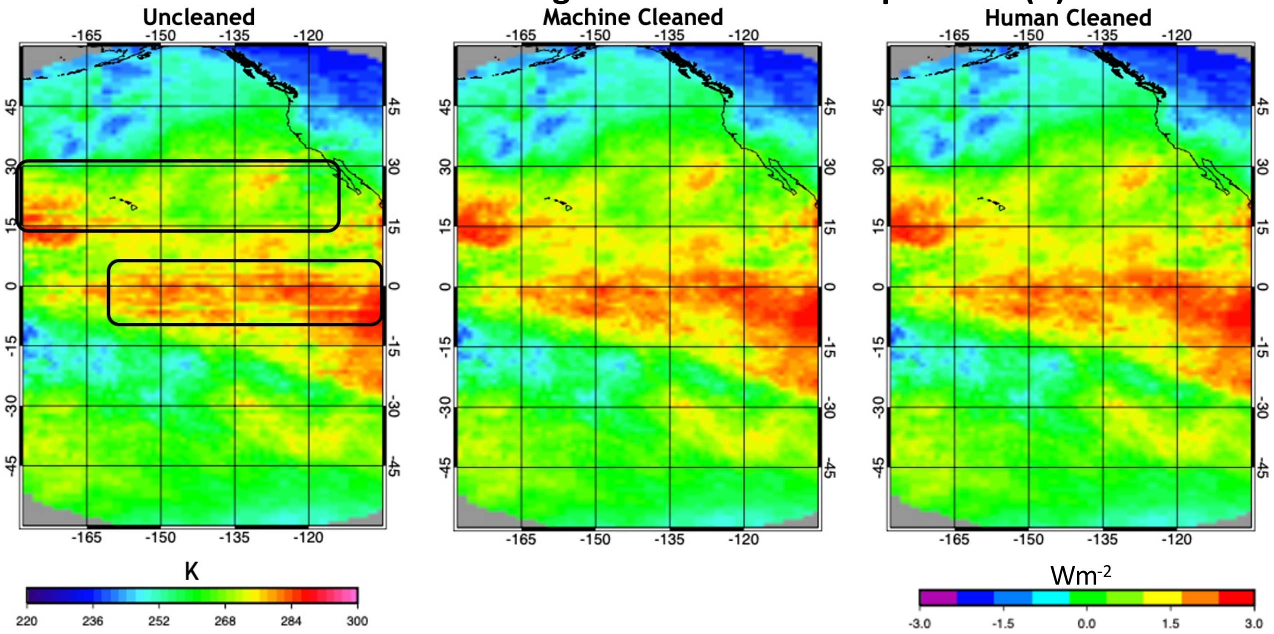
Solution:

- Train a **Convolution Neural Network (CNN)** to identify and "clean" bad scanlines

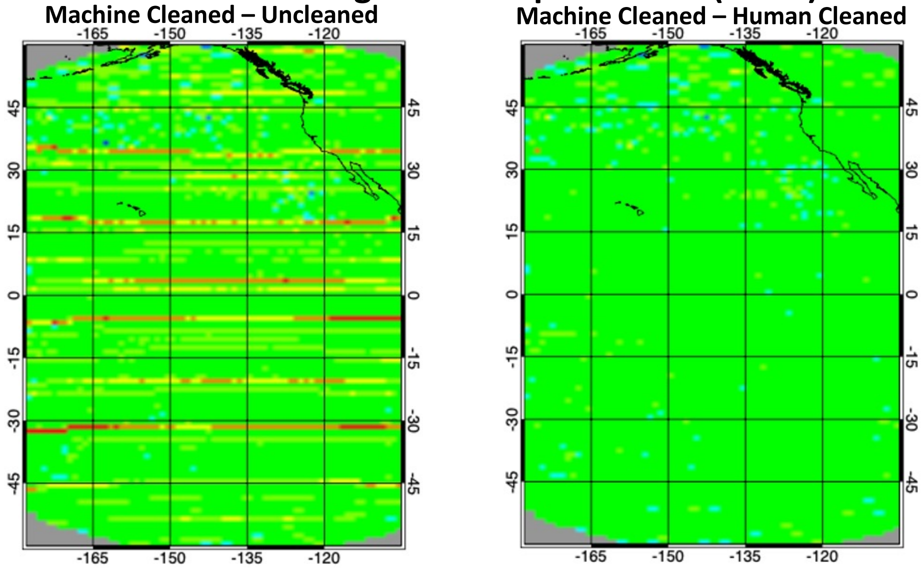
Outcomes:

- CNN approach effectively eliminates artifacts in derived products (CERES-Syn1deg shown here)
- Much more efficient and at least as accurate as manual approach

CERES SYN1deg Cloud Effective Temperature (K)



CERES SYN1deg TOA LW Upward Flux (Wm^{-2})



Feb 2021 Monthly Means

Image Quality – bad scan lines

Problem:

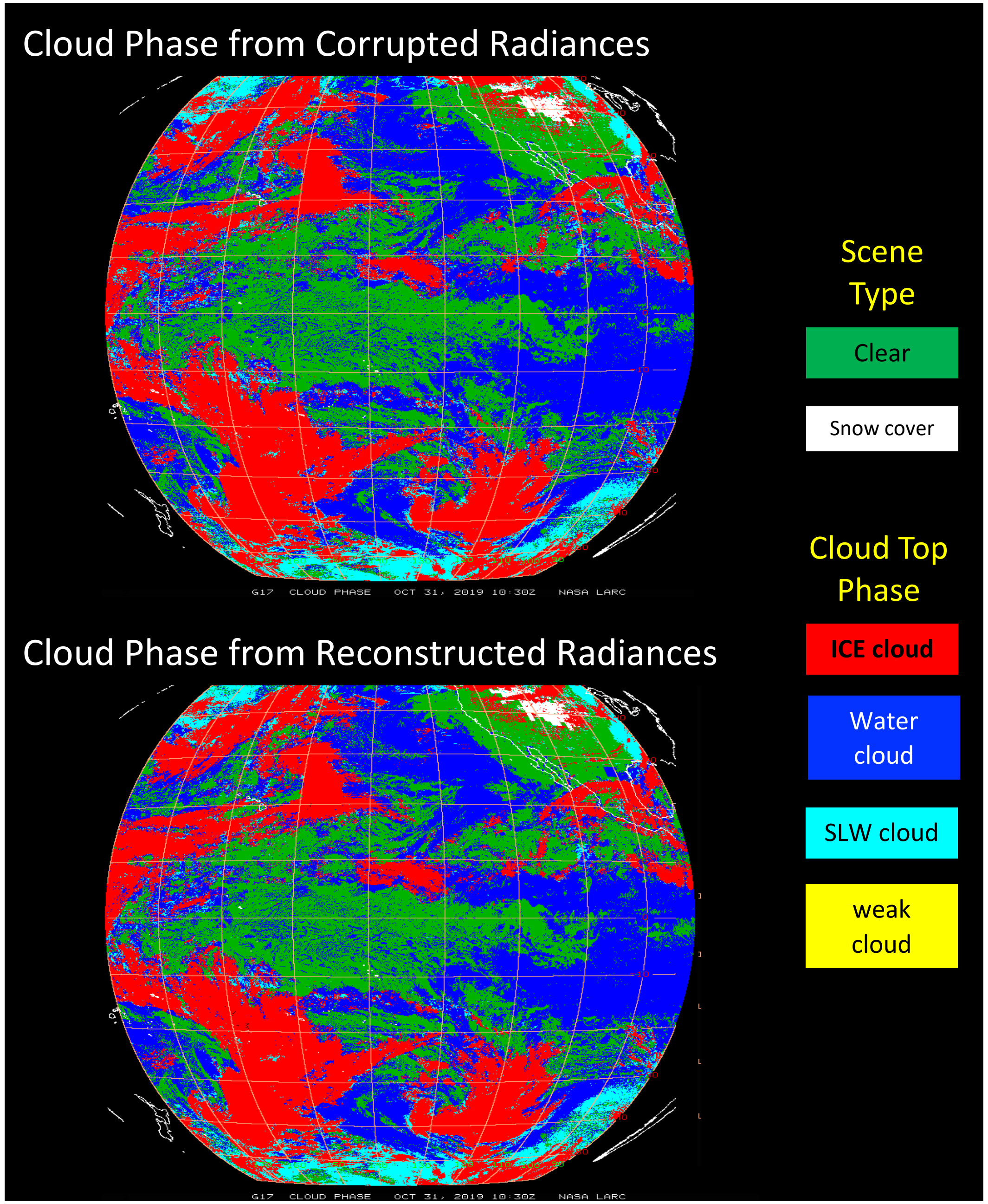
- **GOES-17 cooling system anomaly creates many bad scanlines – leads to bad cloud retrievals**

Solution:

- Apply **K-Nearest Neighbor (KNN)** to reconstruct the corrupted bands by extrapolating data from unaffected image times that occur before/after cooling anomaly - requires at least 1 unaffected IR band (e.g. 10.2 µm)

Outcomes:

- Nighttime cloud properties derived from the reconstructed radiances have similar accuracies as the standard cloud properties (demonstrated using GOES-16).
- Enabled effective use of GOES-17 nighttime data in CERES operations



Deep Neural Network for Land Skin Temperature

Background:

- Threshold approaches for cloud detection rely on an estimate of the surface emission land surface temperature (LST) which is often obtained from NWP/reanalysis data

Problem:

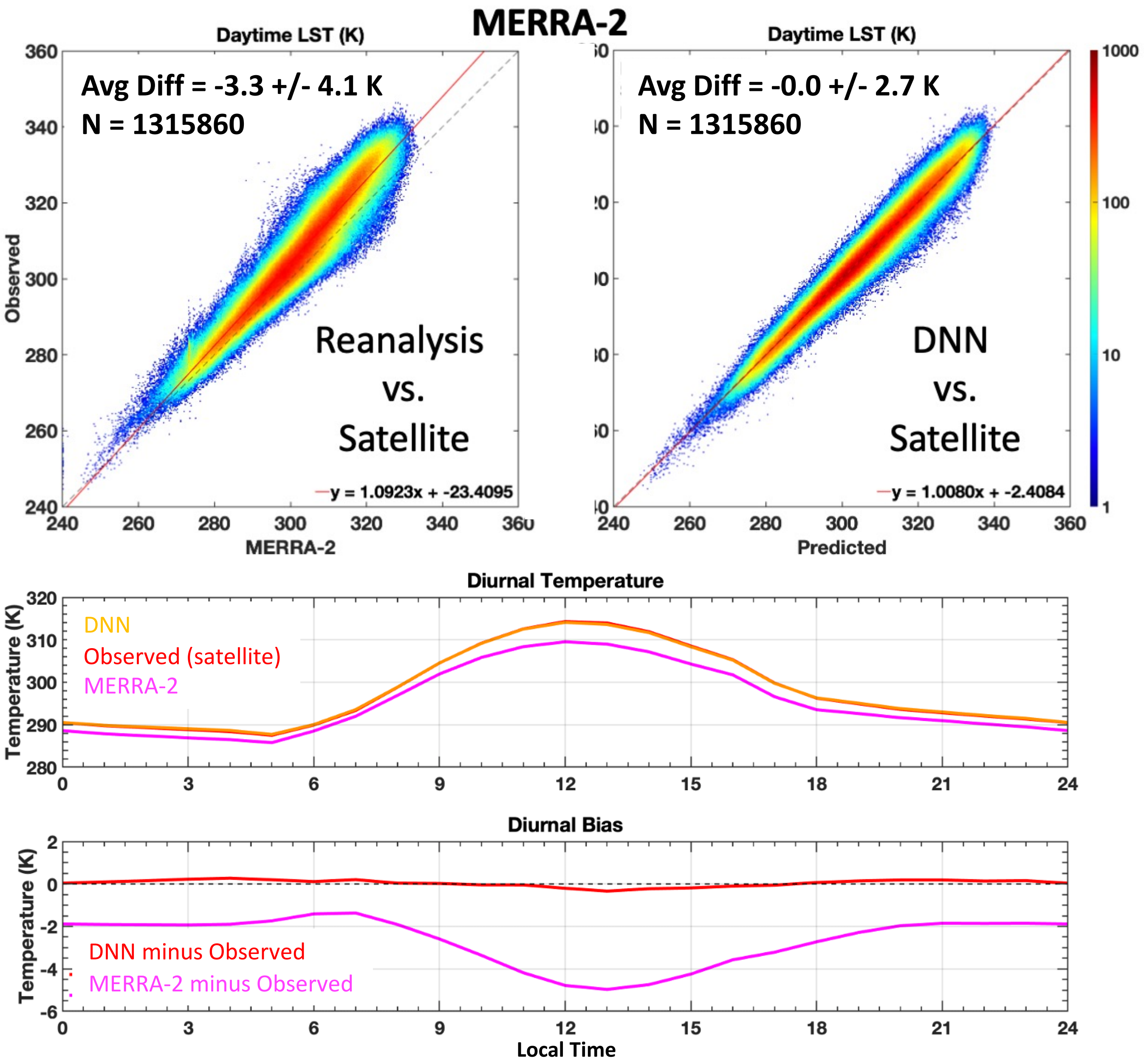
- Models and observations found to disagree in clear conditions (diurnal dependence)
- Differences vary among models but significant for all

Solution:

- Train Deep Neural Networks to tie reanalysis air temperature to satellite-observed skin temperature (LST) in cloud free conditions

Outcome:

- DNN approach effectively removes diurnally dependent regional differences found between reanalysis LST's and observations
- Should lead to improved regional accuracies in cloud detection



Detecting and Retrieving Multilayer (ML) Cloud Properties

Artificial Neural Network Approach

Background:

- CERES developed and applied a theoretical ML retrieval algorithm to Aqua & Terra MODIS data

Problem:

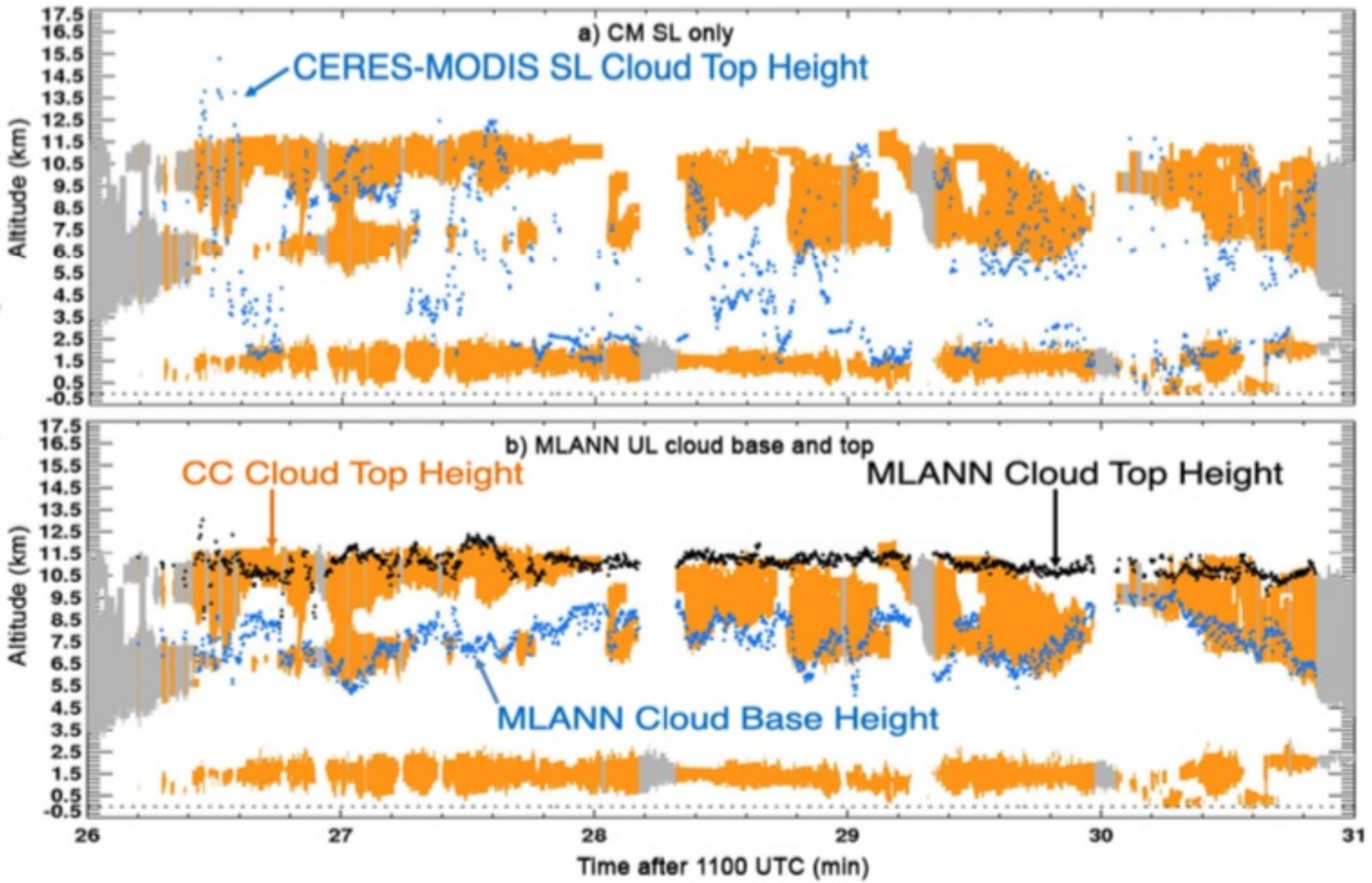
- While height and optical depth retrievals for 2-layer systems were found to be reasonably accurate, the method had very poor skill in discerning ML from SL clouds (no practical value)

Solution:

- Train ANN to discern ML systems from SL systems using CloudSat CALIPSO data as ground-truth

Outcome:

- ANN better detects overlapping thin cirrus than previous method
- ML detection accuracy 75-80% (big improvement)
- Top/base heights for upper layer more accurate
- Is this accurate enough for applications? TBD

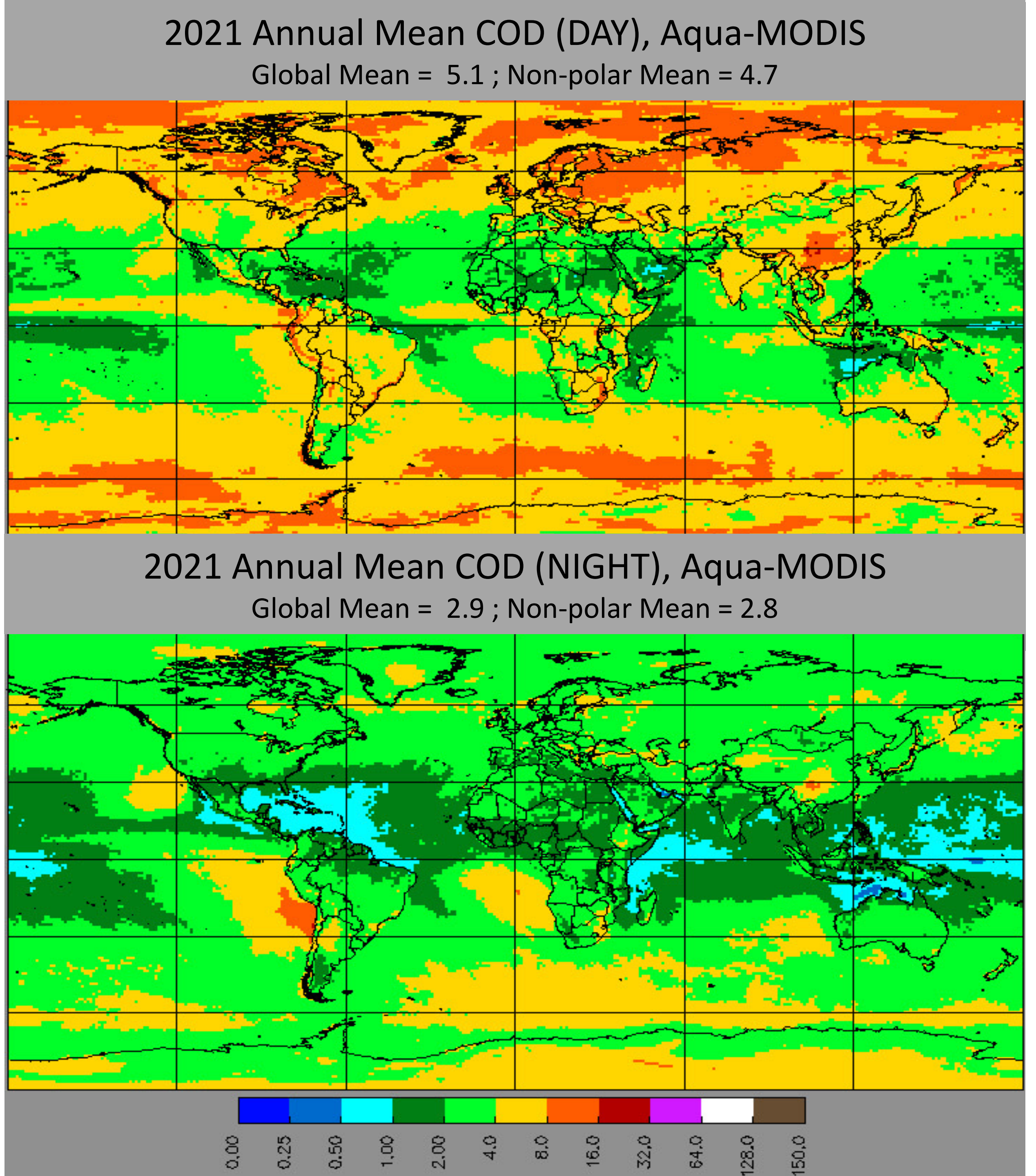


Nighttime Cloud Optical Depth (COD)

Poor consistency between daytime and nighttime

Problem:

- COD can be estimated theoretically from solar channels over a wide range during daytime
- At night, only thin cloud retrievals are theoretically possible (COD < ~6) due to IR blackbody limit
- Optically thick COD's set to pre-assigned fill values (not consistent with daytime retrievals)
- Other parameters derived from COD at night also inconsistent and less accurate than daytime (e.g. CWP, SFC LW↓, icing threat)



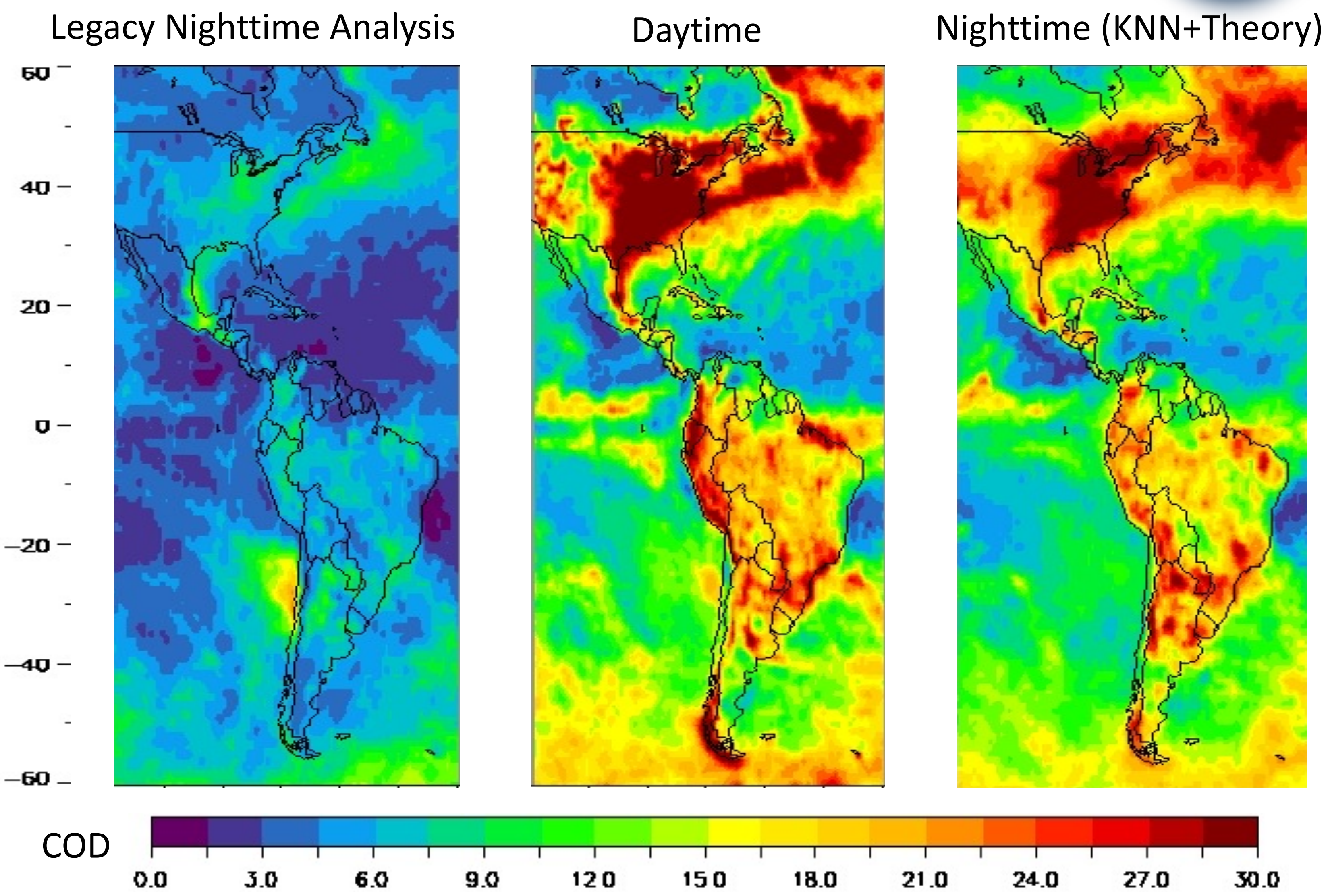
KNN Improves Nighttime Cloud Analyses

Solution:

- Apply **KNN** to extrapolate daytime COD into nighttime using 6.7 and 11 µm bands and local relationships with daytime COD

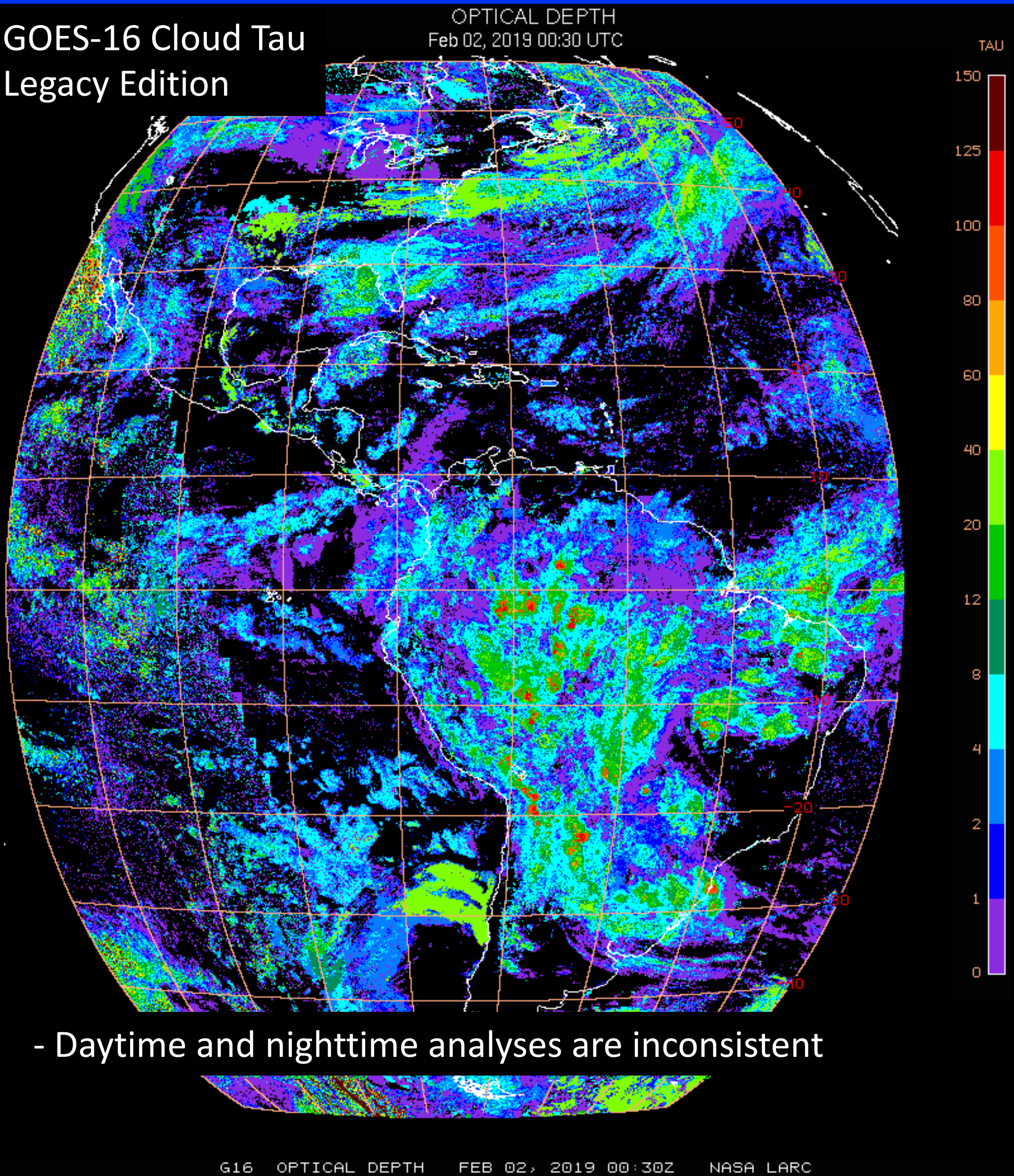
Outcome:

- Much more realistic filling method for nighttime optically thick COD
- More accurate downstream derived parameters



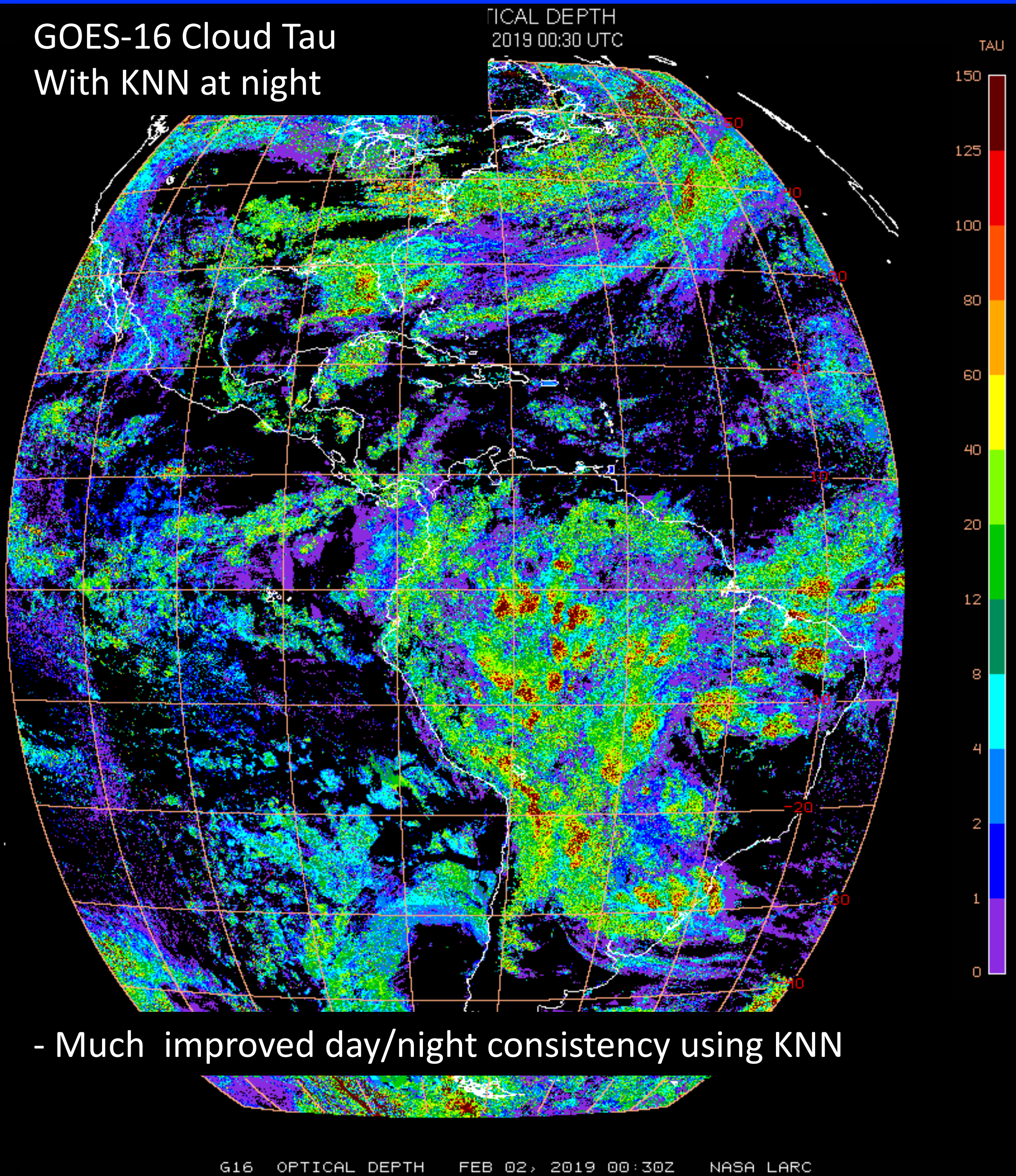
GOES-16 Cloud Optical Depth (Feb 2019)

GOES-16 Cloud Tau
Legacy Edition



- Daytime and nighttime analyses are inconsistent

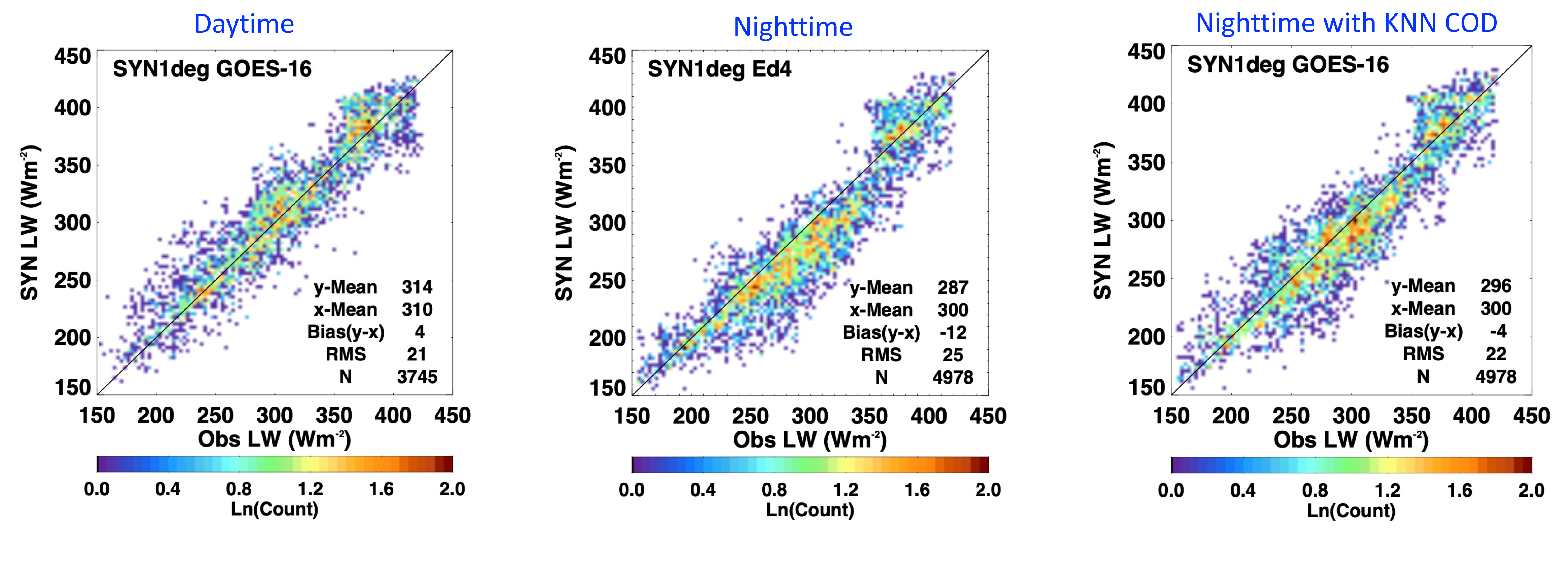
GOES-16 Cloud Tau
With KNN at night



- Much improved day/night consistency using KNN

KNN COD Improves CERES DLWF at Night

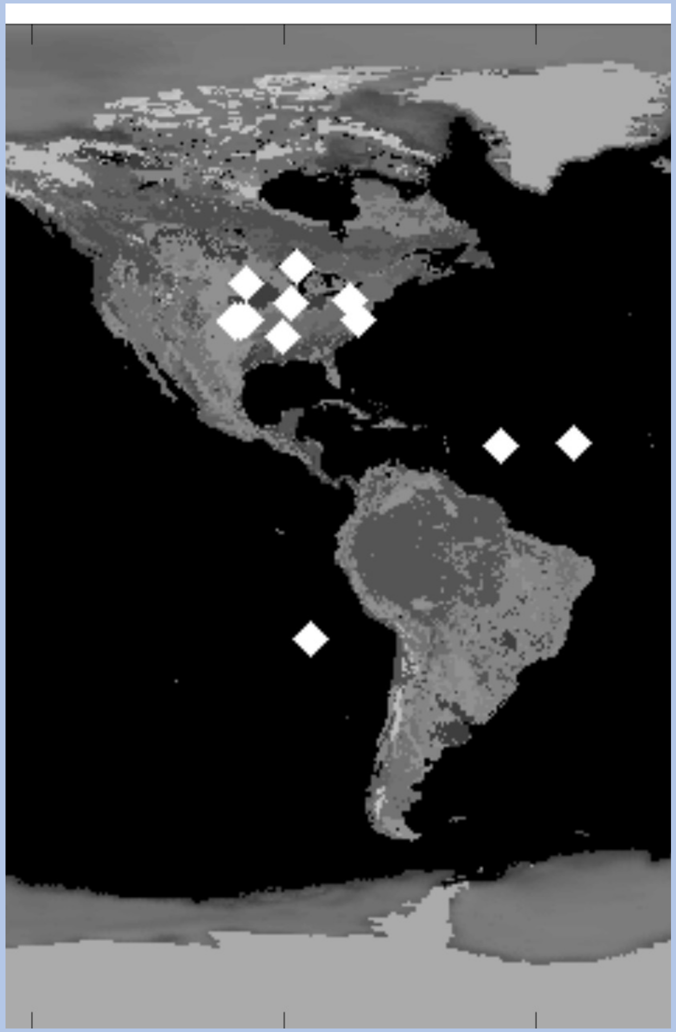
GOES-16 domain, Feb 2019



Computed vs Observed Downward LW Flux

Feb 2019

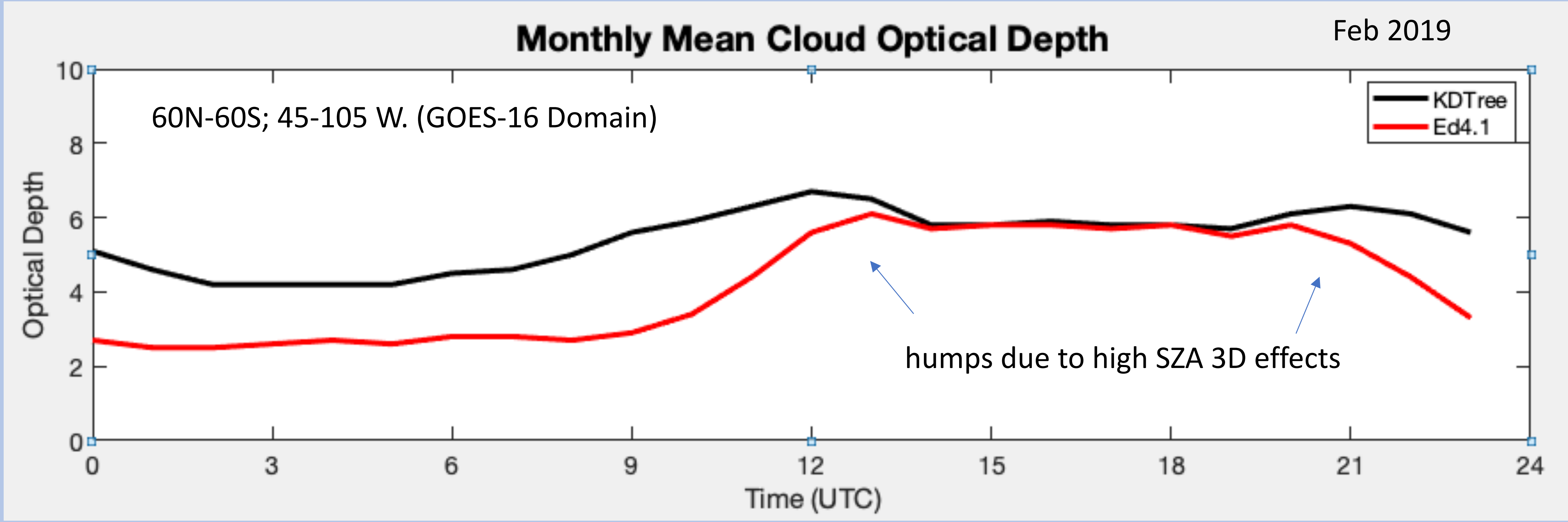
Surface Sites



Site	Ed4 Bias	KNN Bias	Ed4 sdev	KNN sdev
Bondville	-16	-7	22	23
E13	-11	-4	23	22
E9	-19	-11	22	21
E11	-9	-3	24	23
E12	-11	-4	22	21
E15	-13	-7	24	23
Goodwin Ck	-14	-6	16	17
Granite Isle	-31	-23	30	26
Penn St	-10	-3	22	21
Langley	-8	-2	21	20
Sioux Falls	0	5	20	19
Pirata Buoy	9	9	14	14
NTAS Buoy	7	8	12	12
Stratus Buoy	12	14	24	24

SYN1deg COD Diurnal Cycle

GOES-16 domain, April 2019

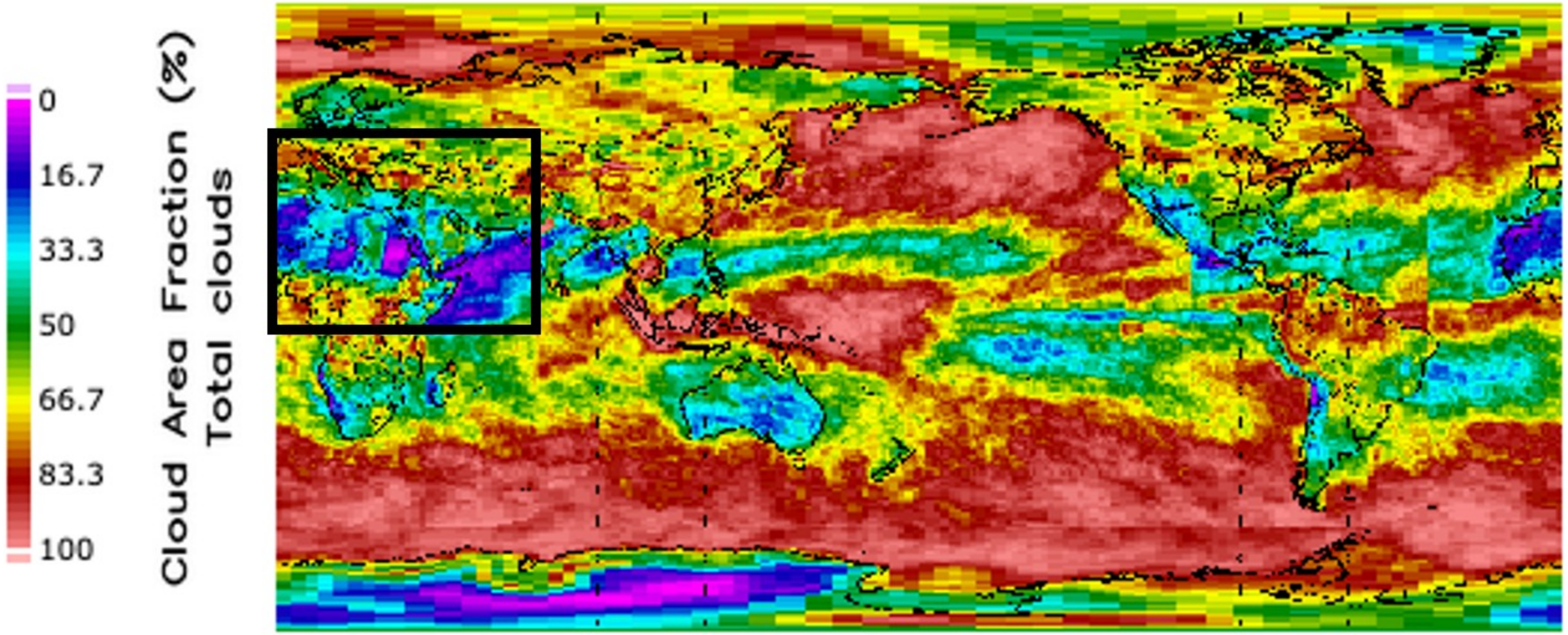


- SYN1deg replaces GEO hour boxes with MODIS data when available but the MODIS nighttime COD has not yet been updated with AI/ML
- Ed4 MODIS data somewhat reduce the GOES-16 KDTree impacts in SYN1deg

Need to adjust the MODIS nighttime COD in a similar way as GEO

Cloud mask over detects in twilight conditions

SYN1deg, April 2019 Monthly hourly (1430 UTC) mean cloud fraction

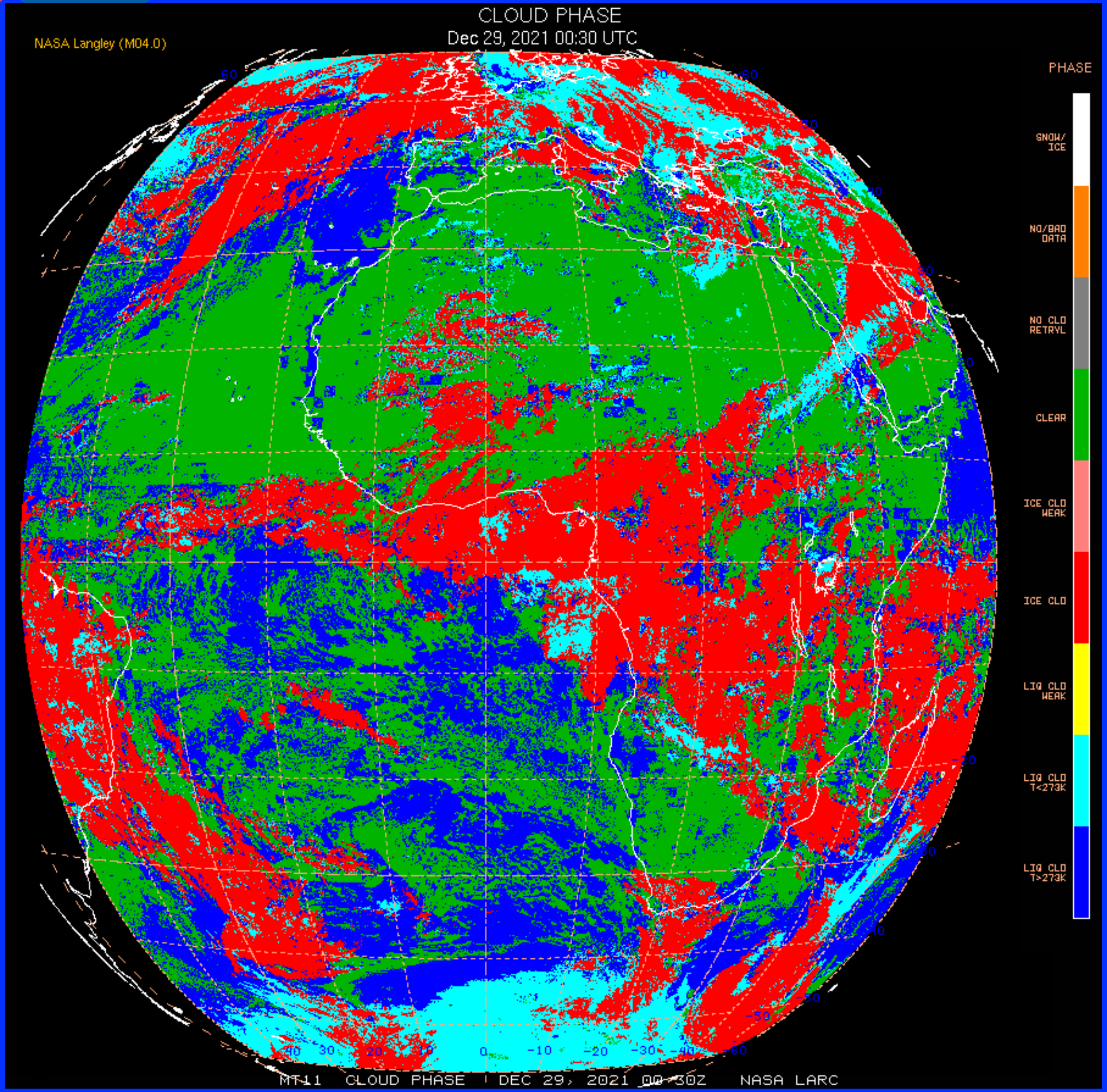


Leads to artificial CF patterns in some regions (e.g. stripes over Sahara)

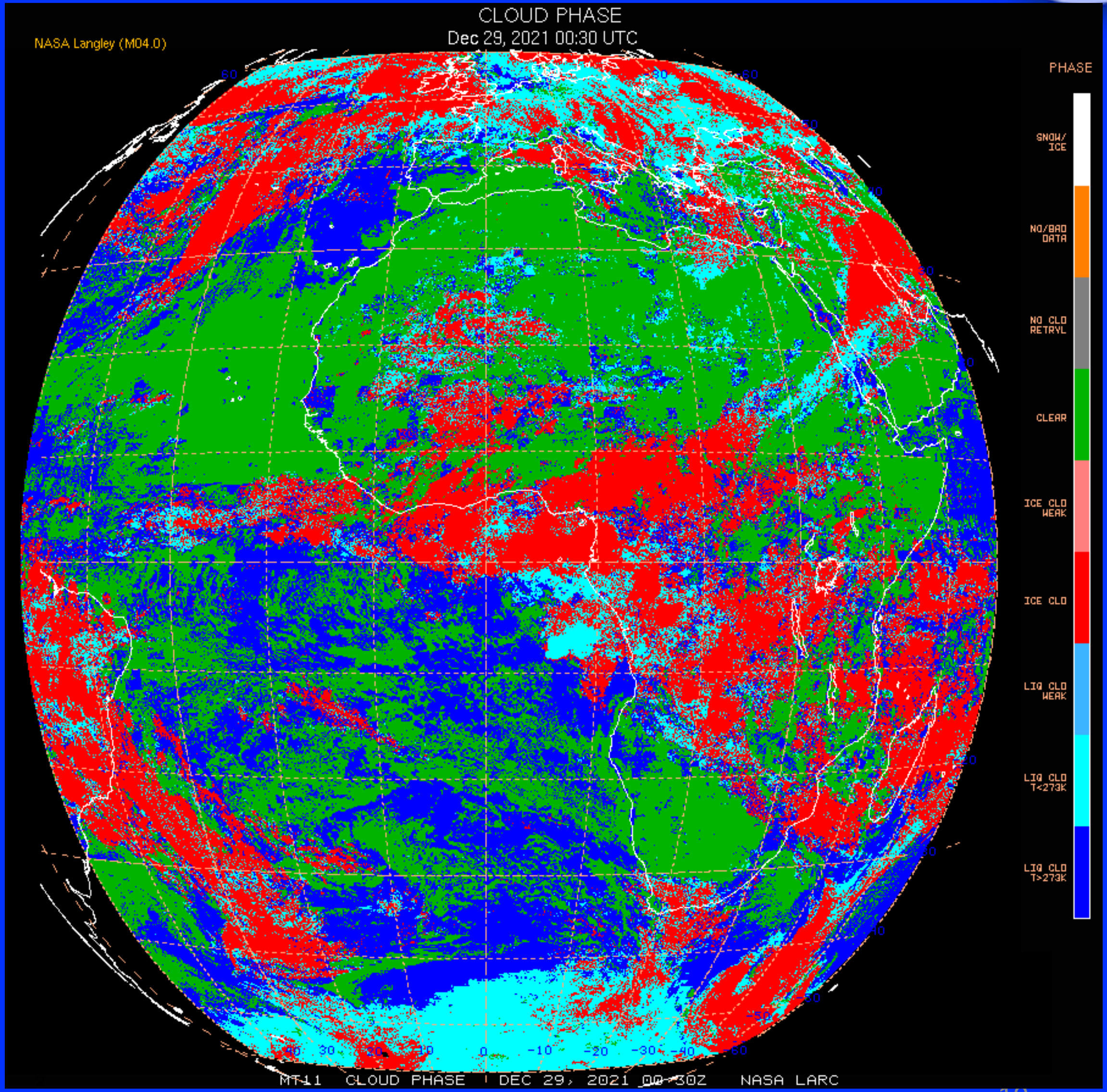
KNN significantly reduces terminator artifacts

MET-11 Dec 29, 2021

Cloud Phase (Ed4 method)



Cloud Phase (with KNN)



Summary

- Very good progress has been made to improve ancillary datasets and cloud retrieval algorithm components for Ed5 that will improve cloud property accuracies and cross-platform consistency
- Cloud mask cross-platform consistency is a significant remaining hurdle. More work is needed to normalize IR radiance observations and clear sky calculations to avoid the need to subjectively tune the mask for 24 satellites
- Within CERES, various AI/ML tools are being developed and used to correct level 0 satellite radiance artifacts and to derive more accurate level 2 cloud and radiation data products.
- Neural nets and KNN enable us to better address common passive satellite remote sensing challenges that have proven difficult using more conventional methods.
- Some of these are ready for implementation and use (e.g. nighttime COD, skin temperature), others need more work and testing (e.g. multilayered clouds, cloud thickness)
- Sunny Sun-Mack will report progress on an ANN approach for polar night cloud detection (Friday morning)

QUESTIONS ?